



**Problem:** Propagation of uncertainty through a real valued, continuous function

$$y = G(a, b)$$

of two real parameters  $a, b$ . Specification of uncertainty of  $a, b$  by: intervals, sets of intervals, probability distributions, sets of probability distributions, or a combination thereof.

**A-priori choice of interpretation:**

*“sets of intervals with equally credible sources”  
= “random set with uniform weights”.*

**Our approach:** Interpret all types of uncertainties of the input data as sets of probability measures.

**Output:** lower and upper probabilities

$$\underline{P}(y \in C) \leq \overline{P}(y \in C)$$

for arbitrary Borel sets  $C \subset \mathbb{R}$ .

**The univariate case**

*Hypotheses:*  $G : \mathbb{R} \rightarrow \mathbb{R}$  is a continuous function,  $y = G(a)$ ;  $C$  is a Borel subset of  $\mathbb{R}$ .

*Consistency:*  $\underline{P}, \overline{P}$  coincide with the usual interpretation – endpoints of intervals, belief and plausibility, necessity and possibility.

**Intervals:** The uncertainty of  $a$  is specified by a closed interval  $A \subset \mathbb{R}$ . Then

$$G(A) = [\inf\{G(x) : x \in A\}, \sup\{G(x) : x \in A\}].$$

The upper probability is

$$\tilde{P}(y \in C) = \begin{cases} 1, & G(A) \cap C \neq \emptyset \\ 0, & G(A) \cap C = \emptyset. \end{cases}$$

Interpreting  $A$  as the set  $\mathcal{M}$  of all probability measures on  $A$ , the corresponding upper probability is

$$\begin{aligned} \overline{P}(y \in C) &= \sup\{p(G^{-1}(C)) : p \in \mathcal{M}\} \\ &= \tilde{P}(y \in C). \quad (\text{Consistency}) \end{aligned}$$

**Random sets:**  $a$  is modeled by a random set with focal sets  $A^i$  and weights  $m(A^i)$ . Plausibility measure:

$$\tilde{P}(y \in C) = \sum_{G(A^i) \cap C \neq \emptyset} m(A^i).$$

Alternatively,  $a$  is the set of probabilities of the form  $p = \sum m(A^i)p_i$  where each  $p_i$  belongs to the set  $\mathcal{M}^i$  of probability measures on  $A^i$ . Upper probability:

$$\begin{aligned} \overline{P}(y \in C) &= \sup\{p(G^{-1}(C)) : p = \sum m(A^i)p_i, p_i \in \mathcal{M}^i\} \\ &= \tilde{P}(y \in C). \quad (\text{Consistency}) \end{aligned}$$

**Sets of probability measures:**  $a$  is modeled by a family of probability measures  $\{p_\lambda : \lambda \in \Lambda\}$ . If  $\Lambda$  is just a set, we put

$$\tilde{P}(y \in C) = \sup\{p_\lambda(G^{-1}(C)) : \lambda \in \Lambda\}.$$

If  $\Lambda$  is itself a probability space with a (single) measure  $\pi$ , we define

$$P_\pi(y \in C) = \int_\Lambda p_\lambda(G^{-1}(C)) d\pi(\lambda).$$

If  $\Lambda$  is equipped with a family  $\mathcal{M}$  of probability measures, the corresponding upper probability is defined by

$$\overline{P}(y \in C) = \sup\{P_\pi(y \in C) : \pi \in \mathcal{M}\}.$$

Then always

$$\overline{P}(y \in C) \leq \tilde{P}(y \in C).$$

Equality holds if  $\mathcal{M}$  contains all Dirac measures situated at the points of  $\Lambda$ . (Consistency)

**Fuzzy sets:**  $a$  is a fuzzy set with membership function  $\mu_a : \mathbb{R} \rightarrow [0, 1]$ . Possibility distribution on  $\mathbb{R}$ :

$$\mu_a(B) = \sup\{\mu_a(x) : x \in B\}$$

where  $B \subset \mathbb{R}$ . Wellknown:

$$\mu_a(x) = \sup\{p(\{x\}) : p \prec \mu_a\}.$$

Possibility degree of  $C$  under the function  $G$ :

$$\mu_{G(a)}(C) = \sup\{\mu_a(x) : x \in G^{-1}(y), y \in C\}.$$

Upper probability:

$$\begin{aligned} \overline{P}(y \in C) &= \sup\{p(G^{-1}(C)) : p \prec \mu_a\} \\ &= \mu_{G(a)}(C). \quad (\text{Consistency}) \end{aligned}$$

**The multivariate case**

The joint probability measures are of the form

$$P = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} m(A_1^i \times A_2^j) P^{ij}$$

and have marginals in  $\mathcal{M}_1$ , respectively  $\mathcal{M}_2$ ;  $m$  is the joint weight function and  $P^{ij}$  are measures on  $A_1^i \times A_2^j$ . **The results crucially depend on the notion of independence chosen – the question of interaction becomes decisive and requires a choice!**

Notation: the marginals of  $P^{ij}$  in  $\mathcal{M}_1^i$  and  $\mathcal{M}_2^j$  will be denoted by  $P_1^{i,ij}$  and  $P_2^{j,ij}$ , respectively.

**Strong independence:**

- Joint weights  $m(A_1^i \times A_2^j) = m_1(A_1^i)m_2(A_2^j)$ .
- $P^{ij} = P_1^{i,ij} \otimes P_2^{j,ij}$ .
- $P^{ij}$  satisfies  $P_1^{i,i1} = P_1^{i,i2} = \dots = P_1^{i,in_2}$  and  $P_2^{j,1j} = P_2^{j,2j} = \dots = P_2^{j,n_1j}$ . ★

$\mathcal{M}_S = \{P_1 \otimes P_2 : P_1 \in \mathcal{M}_1, P_2 \in \mathcal{M}_2\}$  is the set of joint probability measures.

**Random set independence (Dempster-Shafer):**

- Joint weights  $m(A_1^i \times A_2^j) = m_1(A_1^i)m_2(A_2^j)$ .
- $P^{ij}$  are arbitrary with marginals in  $\mathcal{M}_1^i, \mathcal{M}_2^j$ .
- Condition ★ is dropped.

**Unknown interaction (correlation):**

- Weights  $m(A_1^i \times A_2^j)$  are arbitrary subject to  $\sum_{j=1}^{n_2} m(A_1^i \times A_2^j) = m_1(A_1^i), \sum_{i=1}^{n_1} m(A_1^i \times A_2^j) = m_2(A_2^j)$ .
- Measures  $P^{ij}$  as for random set independence.

$$\mathcal{M}_U = \{P : P(\cdot \times \mathbb{R}) \in \mathcal{M}_1, P(\mathbb{R} \times \cdot) \in \mathcal{M}_2\}.$$

**Fuzzy set independence:**

- In the case of consonant focal sets a random set  $a_k$  generates a fuzzy set  $\tilde{a}_k$ .
- The re-interpretation of the joint fuzzy set  $\tilde{a} = \tilde{a}_1 \times \tilde{a}_2$  as a random set leads to the same joint focals as above, but in general with different weights.

**Combination of probability measures**

**parametrized by random sets:** Here the set  $\mathcal{M}_k^i$  is a set of probability measures  $p_{a_k^i}$  parametrized by probability measures on the focal set  $A_k^i$ :

$$\mathcal{M}_k^i = \{P_\pi : P_\pi = \int_{A_k^i} p_{a_k^i}(\cdot) d\pi(a_k^i), \pi(A_k^i) = 1\}.$$

For challenge problem 1 the lower and upper complementary cumulative distribution functions  $\underline{F}(y_f) = \underline{P}(y \geq y_f)$  and  $\overline{F}(y_f) = \overline{P}(y \geq y_f)$  are plotted. We use the indices **S**, **R**, **U** and **F** to indicate the different types of independence.

**Relations between the types of independence.**

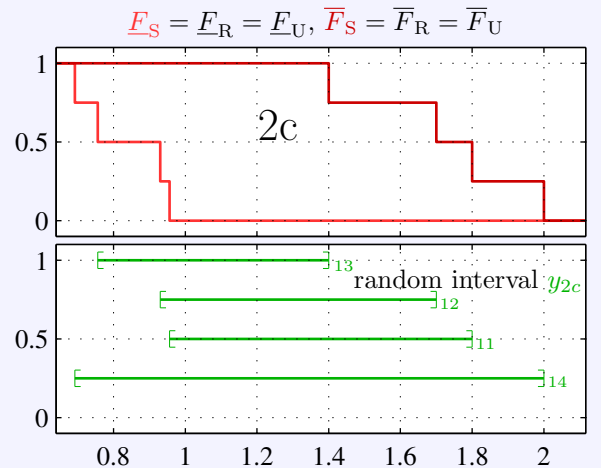
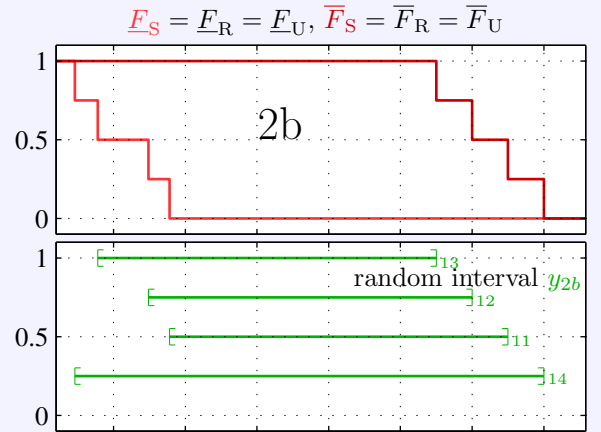
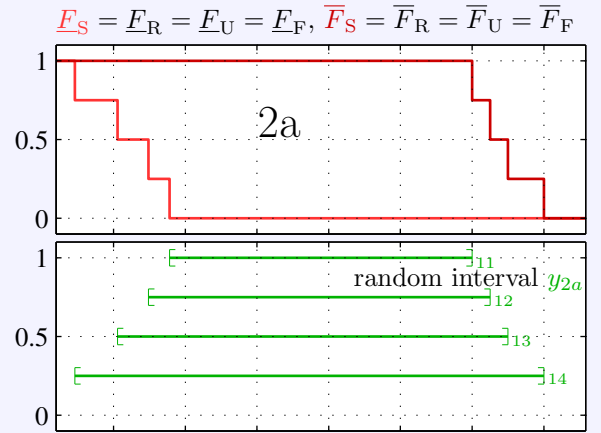
- $\mathcal{M}_S \subseteq \mathcal{M}_R \subseteq \mathcal{M}_U$  and  $\mathcal{M}_F \subseteq \mathcal{M}_U$ ,
- $\underline{F}_U \leq \underline{F}_R \leq \underline{F}_S \leq \overline{F}_S \leq \overline{F}_R \leq \overline{F}_U$  and  $\underline{F}_U \leq \underline{F}_F \leq \overline{F}_F \leq \overline{F}_U$ .

**Problem 1: interval  $\times$  interval.**

$\underline{F}_S = \underline{F}_R = \underline{F}_U = \underline{F}_F, \overline{F}_S = \overline{F}_R = \overline{F}_U = \overline{F}_F$  and resulting interval  $y_1 = [0.6922, 2]$ , see problem 2.

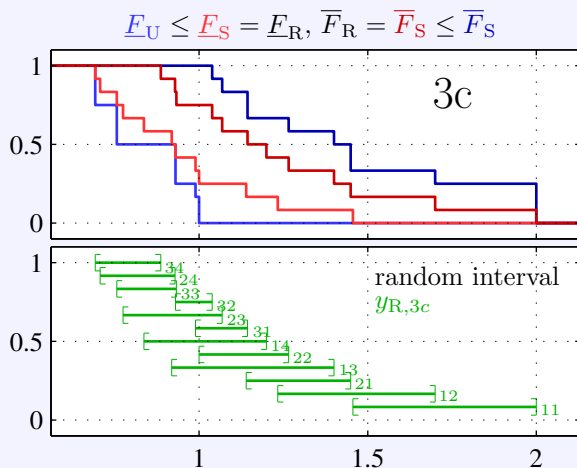
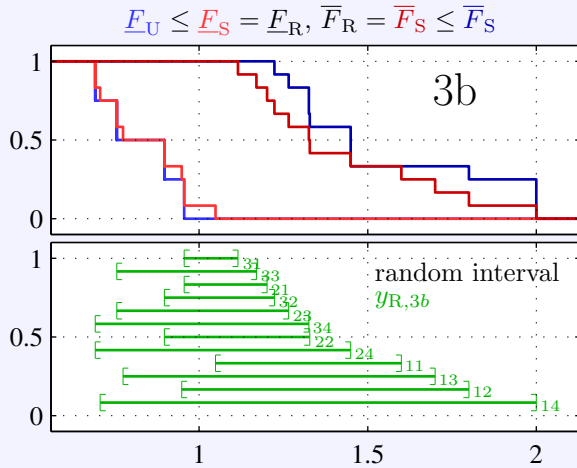
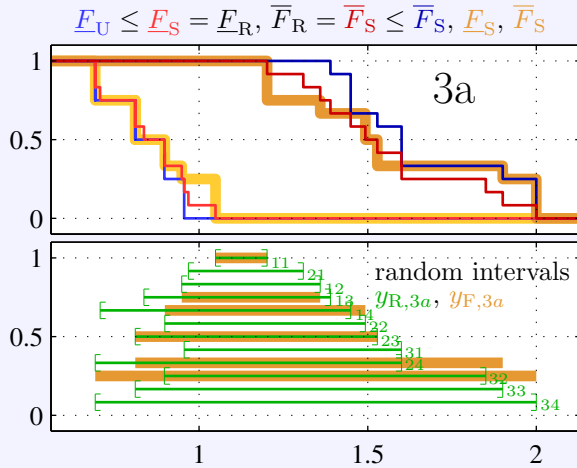
**Problem 2: interval  $\times$  random interval.**

- The joint weights  $m(A_1^i \times A_2^j)$  are unique.
- Due to the monotonicity of  $(a_1 + a_2)^{a_1}$  in the  $a_2$ -direction, dropping the condition ★ does not change the result  $\Rightarrow \underline{F}_S = \underline{F}_R, \overline{F}_S = \overline{F}_R$ .

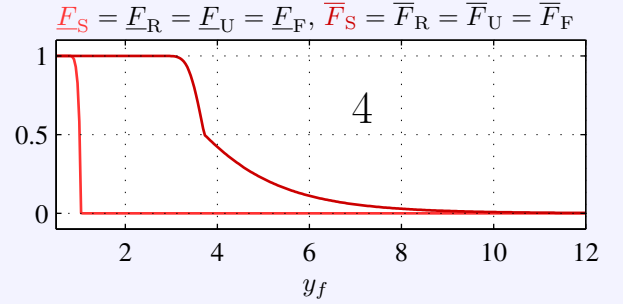


**Problem 3:**random interval  $\times$  random interval.

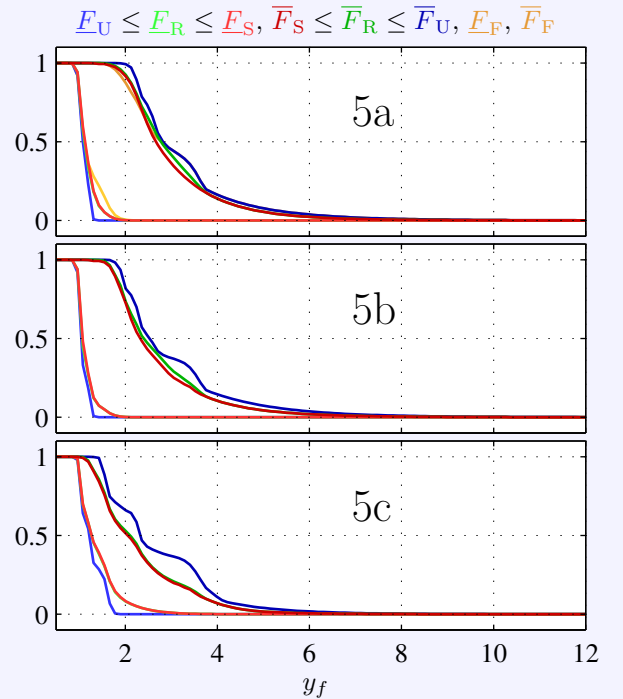
- By the same arguments as in problem 2:  
 $\underline{E}_S = \underline{E}_R$  and  $\overline{F}_S = \overline{F}_R$ .
- The joint weights are not uniquely determined:  
Different results for random set independence, fuzzy set independence and unknown interaction.

**Problem 4:**interval  $\times$  probability measure parametrized by an interval.

- By similar arguments as for problem 1 and 2:  
 $\underline{E}_S = \underline{E}_R = \underline{E}_U = \underline{E}_F, \overline{F}_S = \overline{F}_R = \overline{F}_U = \overline{F}_F$ .

**Problem 5:**random interval  $\times$  probability measure parametrized by a random interval.

- $\overline{F}_S(y_f) < \overline{F}_R(y_f)$  holds for some  $y_f$ .

**Problem 6:** interval  $\times$  probability measure.